Nonpoint Source Pollution Control Programs: Enhancing the Optimal Design Using A Discrete-Continuous Multiobjective Genetic Algorithm

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Nonpoint Source Pollution

Agriculture is among leading contributors to water quality impairments in the U.S. and around the world.

Control of agricultural NPS pollutants can be achieved through implementation of conservation practices, commonly known as best management practices (BMPs).

Strategies for implementing conservation practices:
- Cost-share programs: a field-scale approach
- Targeting critical areas within the watershed
  - Critical source areas
  - Scenario analysis
  - Optimization
Implementation of Conser. Practices

- Cost-sharing with land owners and producers
  - Does not guarantee maximum water quality benefits at the watershed scale

- Targeting using expert recommendations

- Targeting critical areas using geospatial characteristics of areas within the watershed, e.g., soil-topographic index
  - Important watershed processes and interactions amongst practices are not considered
Targeting Using Scenario Analysis

- Full enumeration and evaluation of all possible scenarios may be infeasible even at HUC 12 or similar scales.

- Employing optimization algorithms can facilitate identification of optimal suites of BMPs that reduce pollutant load at minimum cost.

- Multi-objective approaches can expose tradeoffs between often conflicting environmental, socioeconomic and institutional criteria.
Simulation-Optimization Approach

- Binary-variable optimization
- Discrete-variable optimization
- Continuous-variable optimization
- Mixed discrete/continuous-variable optimization
Study Objectives

- To develop a novel heuristic multiobjective optimization method using mixed discrete/continuous decision variables

- To determine improved assessment of environmental and economic tradeoffs using a mixed-variable optimization method compared to a binary optimization approach

- To examine enhanced convergence of the optimization approach by hybridization
Study Area

- Eagle Creek Watershed (ECW), Indiana
  Drainage area: 41.2 km²
Calibration and Testing

- Simulation model: SWAT
- Special attention was paid to accurate representation of hydrologic and water quality processes

<table>
<thead>
<tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>PBIAS (%)</td>
<td>R²</td>
</tr>
<tr>
<td>20</td>
<td>Monthly Nitrate</td>
<td>7.9</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>Monthly Atrazine</td>
<td>-6</td>
<td>0.81</td>
</tr>
<tr>
<td>22</td>
<td>Monthly Nitrate</td>
<td>-22.3</td>
<td>0.89</td>
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<td>Monthly Atrazine</td>
<td>42</td>
<td>0.69</td>
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<tr>
<td>27</td>
<td>Monthly Nitrate</td>
<td>0.59</td>
<td>0.93</td>
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<tr>
<td></td>
<td>Monthly Atrazine</td>
<td>13</td>
<td>0.66</td>
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<tr>
<td>32</td>
<td>Monthly Nitrate</td>
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<tr>
<td></td>
<td>Monthly Atrazine</td>
<td>42.3</td>
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<tr>
<td>35</td>
<td>Daily Streamflow</td>
<td>-12.2</td>
<td>0.78</td>
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</table>
Multiobjective Optimization

- **Method:** Modified Nondominated Sorted Genetic Algorithm II (NSGA-II)

- **Objective functions**
  \[
  \begin{align*}
  \text{minimize } y &= f(x|\theta, I, t_d, T); \text{ Pollutant load(s)} \\
  \text{minimize } C &= g(x|\theta, I, p, r, t_d, T); \text{ Cost(s)}
  \end{align*}
  \]

- **Constraint functions**
  \[
  \begin{align*}
  &\text{Chance opf adoption} \\
  &\text{Management considerations}
  \end{align*}
  \]
Economic Component: Cost

\[ C = C_0 + r_{OM} \times C_0 \left( \frac{1 - (1 + i)^{-t_d}}{i} \right) + C_{OP} \]

- \( C_0 \): implementation cost
- \( r_{OM} \): maintenance cost as a percentage of \( C_0 \)
- \( i \): interest rate/100
- \( t_d \): design lifetime of the conservation practice (years)
- \( C_{OP} \): opportunity cost (e.g. loss of crop production), expressed as
  \[ C_{OP} = \sum_{k=1}^{K} r_k \beta_k \]

- \( K \): number of fields
- \( r_k \): unit price of crop in field \( k \)
- \( \beta_k \): changes in crop production
# Mixed-variable optimization

<table>
<thead>
<tr>
<th>Practice 1</th>
<th>Field 1</th>
<th>Field 1</th>
<th>Field 1</th>
<th>...</th>
<th>Field K</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Practice 1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Practice 2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Practice 3</td>
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<td>2</td>
<td>3</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Practice 4</td>
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<td>0-20</td>
<td>0-20</td>
<td>...</td>
<td>0-20</td>
<td>Continuous</td>
</tr>
</tbody>
</table>

![Diagram of mixed-variable optimization](image)

- **BMP<sub>i</sub>**
- **BMP<sub>j</sub>**
- **n<sub>i</sub>** Discrete
- **n<sub>j</sub>** Continuous
- **x<sub>i<sub>1</sub></sub>** ...
- **x<sub>i<n<sub>i</sub></sub>** ...
- **x<sub>j<sub>1</sub></sub>** ...
- **x<sub>j<n<sub>j</sub></sub>**...
## Representation of Conservation Practices

<table>
<thead>
<tr>
<th>BMP</th>
<th>Parameter</th>
<th>Binary-variable</th>
<th>Mixed-variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fertilizer Management</td>
<td>Application rate reduction (%)</td>
<td>20</td>
<td>0-30 (Continuous)</td>
</tr>
<tr>
<td>Grassted Waterways</td>
<td>Width (m)</td>
<td>15</td>
<td>10, 15, 25 (Discrete)</td>
</tr>
<tr>
<td>Grade Stabilization</td>
<td>Height (m)</td>
<td>1.2</td>
<td>1.2 (binary)</td>
</tr>
<tr>
<td>Tillage/Residue management</td>
<td>Type</td>
<td>Conservation</td>
<td>Conventional</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Conservation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>No-till (Discrete)</td>
</tr>
</tbody>
</table>
Optimization Operation Parameters

- Population size = 100+
  - Parallel runs

- Crossover probability = 0.5

- Mutation rate = 0.005

- Termination conditions: 30 consecutive runs with less than 0.01% improvement in objective function values and decision space
Results

- Mixed-variable approach improved load reduction by 20-25%.
- Mixed-variable approach identified solutions with up to 40% lower cost for the same level of pollutant load reduction as compared to the binary-variable approach.
Convergence
Hybridization

- Hybridization of modified GA with gradient-based local search method
  - GA-based optimization methods guarantee "convergence" but not "optimality"
  - Does not work with discrete-variables problems
Enhanced Convergence by Hybridization

- The Hybrid method terminated in 66 generations after the binary optimization solutions were identified.

- Nearly 30 times faster than the mixed-variable NSGA-II.
Comparison of the objective space

• Lebesgue measure ($n$-dimensional volume)

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Lebesgue Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binary</td>
<td>$4.54 \times 10^8$</td>
</tr>
<tr>
<td>Mixed</td>
<td>$5.71 \times 10^8$</td>
</tr>
<tr>
<td>Hybrid</td>
<td>$5.78 \times 10^8$</td>
</tr>
</tbody>
</table>

![Graph showing comparison of objective space with data points for different algorithms.](image)
Spatial Distribution of Practices

(1) $17,000 1% 1%

(2) $28,000 1% 4%

(3) $40,000 4% 15%

(4) $96,000 8% 17%

(5) $141,000 12% 18%

(6) $277,000 13% 19%

Costs and load reduction percentages for different management practices are depicted in the maps. The right side of the image shows scatter plots for atrazine and nitrate, indicating the cost ($M) vs. load reduction (%) for various practices.
Additional Notes

- Priority BMPs
  1. Grassed waterways
  2. Fertilizer management
  3. Residue/tillage management

- Tillage/residue management had inverse impact on nitrate load in most of the fields and received the lowest priority
Conclusion

- Tradeoffs between maximizing environmental benefit/load reduction and minimizing Costs are apparent, hence, multi-objective optimization is an effective tool for prioritization of fields and practices on a HUC 12 or similar scales.

- Mixed-variable optimization identified better solutions than binary-variable approach.

- Hybrid algorithms can significantly decrease runtime for complex discrete-continuous optimization problems.